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Policy uncertainties: What investment choice for solar panel producers?

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ABSTRACT

Solar power has achieved great development in the last decade, and it should continue to play a central role in the face of climate change and sustainable development challenges. This paper builds a real options model that provides a microeconomic analytical framework with the Least Squares Monte Carlo (LSM) method to assess the investment choices of a typical solar panel producer in China facing trade and domestic supply- and demand-side policy uncertainties. It builds a baseline scenario and three policy scenarios with decreasing anti-dumping and countervailing charges, constant feed-in tariff (FIT) level and reduced investment cost. A typical producer will have to make an investment decision on building a new production line in five years based on a decision impact analysis within 20 years. The result shows an immediate investment decision for all scenarios. The producer will have higher return from investment in building a solar power plant with a constant FIT. Export is the optimal choice in other scenarios where investment return is lower. After sensitivity analysis, the paper concludes and can be used as a toolkit for solar panel producers and a reference for policy makers to evaluate the impact of policy uncertainties.

1. Introduction

Solar power has achieved important development in recent years. The global installed capacity of photovoltaic (PV) power reached 303 GW, with an annual growth rate of 33%. The average solar module price has fallen by 29%, to 0.41 $/W from 2015 to 2016 (REN21, 2017). Such fast development cannot be dissociated from the increasing implementation of supportive domestic policies, for example, feed-in tariffs (FIT) as solar panel demand-side policy and value-added tax and/or income tax deductions as supply-side policy. The implementation of the Paris climate agreement and the adoption of 2030 Sustainable Development Goals (SDGs) at the international level, together with domestic drivers such as energy security and local pollution abatement, provide strong incentives to anticipate continuous growth in the solar power sector in the future.

China is one of the major countries involved in producing solar panels and developing solar power. Today, 9 of the 10 largest solar panel producers are based in China, with a total market share of 55%. China's total installed capacity of solar power accounted for 26% of the global sum in 2016 (REN21, 2017). China also leads in annual investment. China's major national plans (such as the 12th Five Year Plan and the identification of seven strategic and emerging sectors, where solar power is included) all promote the development of solar power. A strong domestic demand for solar power can be concluded without major uncertainty. However, the fast development of solar power is also accompanied with challenges and uncertainties, such as trade disputes (protective trade measures), increasing competition, and domestic policy changes (in particular, the FIT level). China also faces the particular challenge of overcapacity of solar panel production (H. Zhang et al., 2016). Wrong steps taken to deal with uncertainties may even lead to bankruptcy, where the fall of Suntech, once the largest solar panel producer, is the most cited case. It is important for solar panel producers to develop toolkits to anticipate and address market and policy uncertainties and for government to evaluate policy impacts on solar panel producers.

There are many studies on solar power development in the economic literature. They cover a wide range of topics, including the contribution of solar power to climate change (Duan et al., 2016) and to economic development (Algieri et al., 2011); policy instruments (Bonneville and Rialhe, 2005; Leung et al., 2009; Wan and Green, 1998; Lin and Wesseh, 2013; Solangi et al., 2011; Moosavian et al., 2013; Grau et al., 2012); domestic development challenges (Timilsina et al., 2012; Bertsch et al., 2017; Zhou et al., 2016); and trade measures (Liu et al., 2016; Voituriez and Wang, 2015). M.M. Zhang et al. (2016) assessed solar power investment decisions under (carbon, electricity, etc.) price and cost uncertainties. To our knowledge, there is so far no research on the investment choices of solar panel producers facing market uncertainties.

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This paper builds a real options model that provides a microeconomic analytical framework with the Least Squares Monte Carlo (LSM) method (follows Longstaff and Schwartz, 2001; Cortazar et al., 2008; Zhu and Fan, 2011) to examine the investment choices of a typical solar panel producer in China facing trade and domestic supply- and demand-side policy uncertainties. Under scenarios with different assumptions on the FIT level, investment cost and anti-dumping and countervailing duty levels, the model assesses, first, whether a solar panel producer decides to invest in a new production line and, second, if a new production line is established, the optimal choice among selling solar panels to domestic markets, selling to international markets, and investing in solar power stations with solar panels produced by the producer himself.

This paper is organised as follows. Section 2 presents the method; Section 3 shows the data and scenarios; Section 4 discusses the results; and Section 5 demonstrates the sensitivity analysis before concluding.

2. The model

2.1. General presentation

Black and Scholes (1973) and Merton (1973) developed early real options approaches to investigate the price-setting issue of financial products. This approach was later used in different areas of study. For example, Brennan and Schwartz (1985) adopted this approach to assess investment in natural capital. Abadie and Chamorro (2008) introduced this method to analyse the choice of an electricity producer between the installation of carbon capture and the storage and purchase of carbon emission quotas from the carbon market.

Our model is developed referring to Fuss et al. (2008), who examined the investment choice of carbon capture and storage. The model of this paper reflects the fact that solar panel producers may face a decision dilemma of whether to expand new production lines facing the uncertainties of domestic (feed-in tariff changes and policies affecting production costs, e.g., firm income tax reduction) and international trade challenges, particularly anti-dumping measures. The producer has option to decide whether to invest in building a new production line of solar panels and, if so, when to carry out such an investment (the option to defer). As the production line will be phased out over time with the presence of technology improvement, a typical solar panel producer will have to make a decision on whether and when to expand into a new production line. The decision is affected by the present value of the total net return during the entire lifetime of the production chain according to the different years when the potential investment is made. The year where the investment ensures the highest present value is considered the optimal investment decision in this model. Certainly, if none of the years investigated provide a positive present value of the total net return, the producer will not invest in new production lines. Furthermore, the difference between our solution and that of Fuss et al. (2008) is that the expected future value is determined by a revised Least Squares Monte Carlo simulation method (instead of using the value obtained from the next simulation period).[1]

The model assumes that a rational solar panel producer decides whether and when to invest in the production line. The decision based on real options of this model is A and $a_t \in A$. $a_t = 1$ denotes the producer will invest in the line in year t and $a_t = 0$ denotes the producer will not invest. After the investment is made, the producer chooses one of three possible options each year to maximise its profit: sell all his products in the domestic market; sell all his products in the international market; or use all his products to build a solar power station (where profits come from selling electricity). In reality, a single solar producer may simultaneously conduct these exclusive choices; this is out of the scope and capacity of our analytical framework. The value of the investment is defined by Eq. (1).

$$V = \max_{a_t, b_t} \left\{ e^{-rt} \left[\sum_{t=t_i}^{L_f} \left(e^{-r(t-t_i)} \cdot E(CF_t) \right) - IC \right] \right\} \tag{1}$$

where t_i denotes the year when investment of production line expansion is made; L_f is the lifetime of the new solar panel production line; CF_t is the gross return (from selling solar panels or from selling electricity from the producer's own investment in a solar power station) in year t; IC is the investment cost of a new solar panel production line.

In Eq. (1), B denotes the set of feasible operational actions from which the investor can choose, and b_t is the action chosen in year t. Only after $a_t = 1$, which means the production line investment is made, the producer can choose operational decision in set B. $b_t = 1$ and $b_t = 2$ represent that the producer will sell all his solar panels from the new production line to domestic and international markets, respectively. If $b_t = 3$, the producer will use all the solar panels produced from his new production line to build a solar power plant and sell electricity to the grid. $b_t = 4$ indicates that the producer stops the new production line in year t (in case of a negative net return).

2.2. Treating uncertainties

The model addresses four uncertainties. First, we assume that both the international and the domestic sale prices of solar panels follow the geometric Brownian motion and are described by Eq. (2). Such a treatment can be found in Fuss et al. (2008), Fan and Zhu (2010), H. Zhang et al. (2016) and M.M. Zhang et al. (2016).

$$dP_t^{In,Do} = u_{In,Do} P_t^{In,Do} dt + \sigma_{In,Do} P_t^{In,Do} dW_t^{In,Do} \tag{2}$$

In Eq. (2), $P_t^{In,Do}$ is the sale price of solar panels in the international market and the domestic market in year t, and $E(P_t^{In,Do}) = P_0^{In,Do} e^{u_{In,Do} t}$; $u_{In,Do}$ is the drift parameter representing the expected growth rate of the international and domestic price; $\sigma_{In,\ Do}$ denotes the volatility of the international and domestic price; $dW_t^{In,Do}$ is the increment of a standard Wiener process.

The link between $P_{t+1}^{In,Do}$ and $P_t^{In,Do}$ is given by Eq. (4), and the deduction is given in Annex 1.

$$P_{t+1}^{In,Do} = P_t^{In,Do} \cdot exp\left[\left(u_{In,Do} - \frac{(\sigma_{In,Do})^2}{2} - \lambda \right) \Delta t + \sigma_{In,Do} \varepsilon (\Delta t)^{1/2} \right] \tag{3}$$

Second, the solar power on-grid sale price is fixed by feed-in tariffs set by the central government in China. Feed-in tariffs were first introduced in 2011 and were reduced in 2013 and 2016 as costs continued to fall. The model sets the initial FIT_t based on historical data, and FIT_t decreases with a probability α and a level ω, which is shown by Eq. (5).

$$dFIT_t = \begin{cases} 0, Probability : 1-\alpha \\ \omega \cdot FIT_t, Probability : \alpha \end{cases} \tag{4}$$

Third, China's solar panel export has encountered important trade protection measures such as anti-dumping and countervailing duties in recent years (Voituriez and Wang, 2015). In our model, Tr_t denotes the average levels of anti-dumping duty (AD) and countervailing duty (CVD). Tr_t can vary each year and is described by Eq. (6).

$$dTr_t = \begin{cases} +\nu \cdot Tr_t, Probability : \beta_1 \\ -\nu \cdot Tr_t, Probability : \beta_2 \\ 0, Probability : 1-\beta_1-\beta_2 \end{cases} \tag{5}$$

[1] This is explained later in this section.

where β_1 and β_2 mean the probability that Tr will rise or fall every year, respectively. ν represents the extent of the change.

Finally, the production cost C_t^p of solar panels follows the GBM curve, and the volatility represents the uncertainty of production costs. $\underline{C}^p$ is the lower bound of the production cost, as cost reduction may have a limit. In Eq. (7), u_P is the drift parameter; σ_P is the volatility parameter; and dW_t^p is the increment of a standard Wiener process.

$$\begin{aligned}&\text{If } C_t^p \geq \underline{C}^p, \ \ dC_t^p = u_P C_t^p dt + \sigma_P C_t^p dW_t^p \\ &\text{If } C_t^p < \underline{C}^p, \ \ C_t^p = \underline{C}^p\end{aligned} \tag{6}$$

2.3. Model solution

The solar panel producer maximises the sum of the discounted expected future profits of investment in a new production line. $CF_t(b_t)$ denotes the cash flow at year t that the producer can obtain. As elaborated in Section 2.1, when $b_t = 1$, cash flow comes from the international market, and we have

$$CF_t(1) = \left[Q \cdot P_t^{In} \cdot (1 - Tr_t) - Q \cdot C_t^p - SC_t - MC_t\right] \cdot (1 - it) \tag{7}$$

where Q is the annual capacity of the production line; P_t^{In} is the price of solar panels in the international market; C_t^p is the per megawatt production cost of solar panels; it is the firm income tax; SC_t is the switching cost (described by Burnham et al., 2003 and Lam et al., 2004) that indicates the additional cost if the producer decides to change strategies from one year to another (Eq. (8)) (for instance, from sales in the international market to sales in the domestic market); MC_t is the maintenance cost of the production line.

$$SC_t = \begin{cases} 0, b_t = b_{t-1} \\ SC, b_t \neq b_{t-1} \end{cases} \tag{8}$$

Similarly, when $b_t = 2$, cash flow comes from the domestic market, and $CF_t(2)$ can be written as:

$$CF_t(2) = \left[Q \cdot P_t^{Do} \cdot (1 - vt) - Q \cdot C_t^p - SC_t - MC_t\right] \cdot (1 - it) \tag{9}$$

where P_t^{Do} is the price of solar panels in the domestic market, and vt is the value-added tax in the domestic market.

When $b_t = 3$, the producer invests in a solar power plant with solar panels produced by his new production line. The cash flow $CF_t(3)$ can be written as:

$$CF_t(3) = \left\{\sum_{i=t}^{t+L_p} [Q \cdot \theta \cdot (FIT_t - POC_t)] \cdot e^{-rt} \cdot (1 - vt/2) - Q \cdot C_B - Q \cdot C_t^p - SC_t - MC_t\right\} \cdot (1 - it) \tag{10}$$

where θ is the electricity output of one megawatt solar panel per annum; POC_t is the unit operational cost of a solar power station; r is the discount rate; C_B is the per megawatt installation cost of a solar panel module; L_P is the lifetime of a solar power station.

When $b_t = 4$, the production line did not produce in that year. The cash flow in this case is given by Eq. (11).

$$CF_t(4) = -MC_t \tag{11}$$

The choice of optimal strategy $\{b_t\}_{t=1}^{T}$ (where T is the planning horizon) of the solar panel producer in each year can be obtained recursively by solving the Bellman equation:

$$\begin{aligned}&V_t\left(P_t^{In}, P_t^{Do}, C_t^p, FIT_t, Tr_t\right) \\ &= \max_{a_t, b_t}\left\{CF_t(b_t) + e^{-r}E\left[\left(V_{t+1} | P_t^{In}, P_t^{Do}, C_t^p, FIT_t, Tr_t\right)\right]\right\}\end{aligned} \tag{12}$$

Table 1
Data.

Variable	P^{In}[a]	u_{In}	σ_{In}	P^{Do}[b]	u_{Do}	σ_{Do}	C^p
Value	0.3614 \$/W	−0.0962	0.1127	0.335 \$/W	−0.1181	0.084	0.28 \$/W
Variable	u_p	σ_p	$\underline{P}^{In}$	$\underline{P}^{Do}$	$\underline{C}^p$	Q	IC[c]
Value	−0.1430	0.1922	0.08 \$/W	0.08 \$/W	0.05 \$/W	60 MW	5×10^7 Yuan
Variable	FIT	$\underline{FIT}$	α	ω	Tr	β_1	β_2
Value	0.75 Yuan/kWh	0.3 Yuan/kWh	50%	20%	8%	25%	25%
Variable	ν	MC	SC	θ	POC[d]	C_B[e]	L_p
Value	5%	2.5×10^6 Yuan	5%	1.896×10^6 kWh/MW·a	0.3 Yuan/kWh	3.418 Yuan/W	15 years
Variable	r[f]	L_f	er	it[g]	vt[h]		
Value	0.08	20 years	6.75	25%	17%		

[a] Source: Wind Database.
[b] Source: China Photovoltaic Industry Association.
[c] Taken from media report: http://www.cnmn.com.cn/ShowNews1.aspx?id=329030.
[d] Taken from Lin and Wesseh (2013).
[e] Taken from China's photovoltaic industry road map (2016) (in Chinese).
[f] Taken from M.M. Zhang et al. (2016).
[g] Taken from "Corporate Income Tax Law of the People's Republic of China (State Administration of Taxation, 2007)".
[h] Taken from "Provisional Regulations of the People's Republic of China on Value Added Tax (The State Council, 2008)".

$E[(V_{t+1} | P_t^{In}, P_t^{Do}, C_t^p, FIT_t, Tr_t)]$ can be solved with the Monte Carlo method.[2] This method simulates the possible decisions of a solar panel producer facing the uncertainties defined above. The optimal choice of investment time and form can be obtained as the most frequently selected decision from the total decisions simulated.

Finally, for the purpose of a simple demonstration, there are a few additional assumptions. They can be applied to the model without significantly changing the key results of this paper. First, building a solar power station is an instantaneous process and immediately generates cash flow (income). According to the report of LONGI enterprise, the construction time of 2 GW PV module production line is less than 5 months. The production capacity of our model (Q) is 60 MW and it is far less than 2 GW. Second, the cost of building the production line is fixed and well known by the solar panel producer. Third, all electricity generated can be sold to the grid at market price (FIT), while there is no risk of government non-approval of solar power station construction. Fourth, the production line is at the full production rate, and all solar panels can be sold on the market (no stock for producer).

3. Data and scenario

3.1. Data

Table 1 provides related data. In addition to values taken directly from existing sources or databases, there exist a few estimations and assumptions. First, the estimation is in general calculated based on historical data. The level of drift and volatility rates (u_{In}, σ_{In}, u_{Do}, σ_{Do}, u_p, σ_p) are estimated based on historical data (see Annex 2 for details). The production cost is estimated from the annual reports of typical solar panel producers; in this paper, we took major representative firms such as Yingli, LDK Solar and China Sunergy as references. θ (kWh/MW·a) is the electricity output (kWh) of one megawatt installed solar panel

[2] Kaminski (2004) has proved that the Monte Carlo method can obtain the same results as the partial differential equations approach.

per annum, which is estimated based on theoretical deduction (see Annex 3 for details). The exchange rate is calculated as the average 2017 exchange rate based on data from the Bank of China.[3]

Tr is obtained based on export data from China's customs database and anti-dumping and countervailing duties imposed by the EU and the US. The details of the calculation are provided in Annex 4. The level of Tr varies. In this paper, we set the probability of the annual increase and decrease of Tr at 25% (indicating a 50% probability that Tr remains unchanged), with a level of variation at 5% according to our calculations based on historical data.

The FIT level is obtained from the official FIT for solar power in China; in 2017, China implemented three FIT levels at 0.65, 0.75, and 0.85 Yuan/kWh, and in this paper, we take the FIT at 0.75 Yuan/kWh. The probability of an annual decrease of the FIT is fixed at 50%, and the level of decrease is fixed at 20%. These two levels can be observed from historical data (China has adjusted the FIT level for solar power 4 times in the past).

Second, regarding the assumptions, the annual output of the production line (Q) is fixed at 60 MW, and the maintenance cost of a new production line (MC) is fixed at 5% of the investment cost. The changes of marketing channels require extra cost for a typical photovoltaic manufacturing enterprise; here, we refer to switching cost (SC) in our model. This model assumes that the switching cost is 5% of the year's income. Geometric Brownian motion is the most important hypothesis in our model. We use it to describe the future path of the international and domestic price and production cost. In addition, we set up the lower bound for these three parameters ($\underline{P}^{In}$, $\underline{P}^{Do}$, $\underline{C}^{p}$). The lower bound of the FIT ($\underline{FIT}$) is assumed to be 0.03 Yuan/kWh, which is the average cost of thermal power electricity in China.

3.2. Scenarios

This paper sets the following scenarios. S0 is the reference scenario, as it simulates the current situation in China with uncertain future trade measures (anti-dumping and countervailing duties) and a gradually decreasing FIT for electricity from solar power. S1 sets decreasing burdens from trade measures, which can be understood as a result of a decrease of anti-dumping and/or countervailing measures on Chinese solar panels and/or an increase of solar panel export to other countries with no such protective trade measures. S2 sets a constant FIT at 0.675 Yuan/W (the expected value of the FIT in 2018 in S0) to simulate a demand-side policy on solar power development in line with the 2030 Sustainable Development Goals. S3 reduces the investment cost of solar panel production to half of its level in S0 to simulate the effect of a supply-side supportive policy on solar panel production. Such a policy has been used by both central and local governments in China and contributed to important solar panel production capacity increase in recent years in China (Voituriez and Wang, 2015).

As described in Section 2.3, based on the Monte Carlo method, each scenario is run by the model 10,000 times to eliminate errors and identify representative scenario results. H. Zhang et al. (2016) and M.M. Zhang et al. (2016) proved the pertinence of such a method with 10,000 simulations. The starting point of the model is 2017, and the investment decision period is five years, from 2018 to 2022.

4. Result

4.1. Scenario 0: base scenario

Fig. 1a provides the result of the approach with 10,000 simulations. As shown, 5328 simulations lead to a positive decision of investment in a new production line of solar panels. Among these positive decisions, 5241 simulations choose to invest immediately in 2018, while only a few simulations give the result of a late investment in later years: there are 51, 14, 12 and 10 simulations where investment is made in 2019, 2020, 2021 and 2022, respectively. Against the positive decision, it should be noted that 4672 simulations lead to a negative decision concerning new investment. In general, Fig. 1a shows that the optimal choice for a solar panel producer is to invest immediately a new production line in 2018 to maximise profits. The global risk remains relatively high, as the model shows an important share of non-investment decision due to the uncertainties defined (concerning both trade and domestic policies).

Fig. 1b shows investment returns relative to the investment decisions of Fig. 1a. The investment return is a result of the sum of the net present values of returns generated by the new production line over 20 years minus investment costs. As shown, the average return per simulation reaches 18 million in 2018. Comparing to the 2018 level, the per simulation average returns of investment are 0.96, 0.78, 0.76, and 0.37 million for 2019, 2020, 2021 and 2022, respectively. This is coherent with the finding in Fig. 1a, as the earlier the investment is made, the higher the return that can be obtained.

Fig. 1c provides a further breakdown of the region of the investment returns among the 5241 choices (in Fig. 1a) of immediate investment in 2018. As shown, the return of a major part of simulations (3807 simulations) stays in a relatively lower region (below 25 million US$). After this, the return of 1271 simulations falls in a region between 25 and 50 million US$. Higher return can only be found in a small number of simulations. Such a result is logical provided the increasing degree of competition in the solar panel market. We have identified a real case that provides a similar result to our assessment: in 2015, LONGI Solar ensured a turnover of 1000 million US$ with an annual capacity of 2 GW.[4] Taking the arithmetic average, this gives a turnover of 30 million US$ for each 60 MW annual capacity (our model assumption of the annual production capacity of a solar panel production line).

As defined previously, once the new investment is made, the producer makes a choice each year from among different options. Fig. 2 shows the operational choices of the 5241 simulations (Fig. 1a) of investment in a new production line in 2018. Each simulation provides a single pathway in terms of operational choices. For example, we randomly picked two simulation results from among 5241 simulations in Fig. 2. As shown, in 2018, both paths choose to build a solar power plant. From 2019, one simulation (blue curve) chooses to export solar panels until the end of the simulation period, while another simulation path chooses different options (export, domestic sale and temporary shutdown of production from 2027 to 2031).

Putting together all the 5241 pathways in Fig. 2, the option with the highest proportion is considered the optimal operational choice of the year. As shown, the highest proportion in 2018 is represented by the self-invested solar power plant with solar panels produced by the new production line. This is due to the existence of an FIT that is sufficiently attractive for the solar panel producer compared to other options. As the level of FIT decreases, from 2019 until the end of the simulation period, the proportion of export becomes dominant as trade barriers are gradually reduced (see the setting of the scenario above for details).

4.2. Scenario 1: decreasing protective measures in trade

Fig. 3a shows a similar result when the burden of anti-dumping and countervailing measures continues to decrease. Comparing to S0, more simulations lead to an investment decision: in total, there are 5791 simulations of investment decision. Similarly, an immediate investment in 2018 becomes more interesting (5645 simulations in S1 against 5241 simulations in S0) as the solar panel producer anticipates a continuous decrease of costs generated by protective trade measures.

3 http://www.boc.cn/sourcedb/whpj/.

4 Taken from media report: http://www.cnmn.com.cn/ShowNews1.aspx?id=329030.

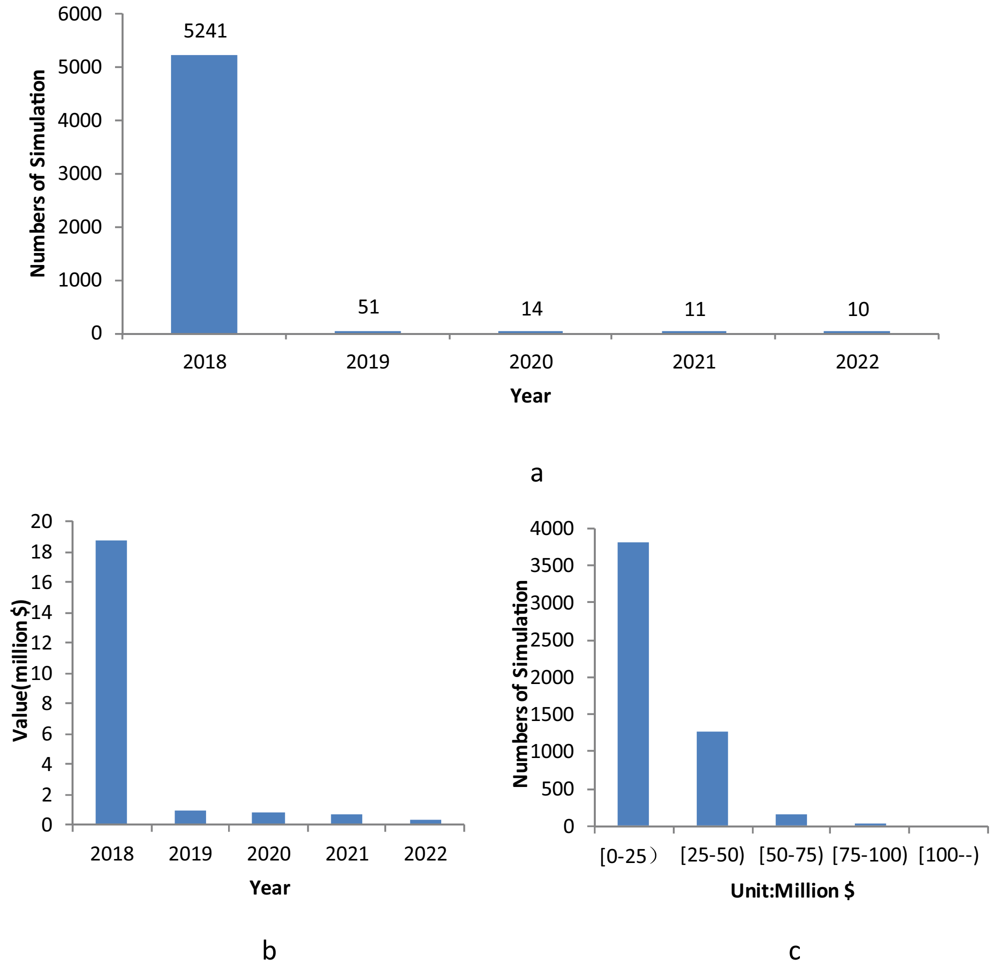

Fig. 1. a: Simulation results of investment year. b: Per simulation investment return. c: The distribution of investment return in the optimal year.

As investment risk becomes lower in S1 relative to S0, investment return is 15% higher in S1 than in S0 (see Fig. 3b) as a result of an increasingly opening international market. Again, the return is much higher for investment in 2018 than for later investments. An open trade market also increases the share of higher return from investment in 2018 (Fig. 3b). Compared to S0, a higher share of investment with

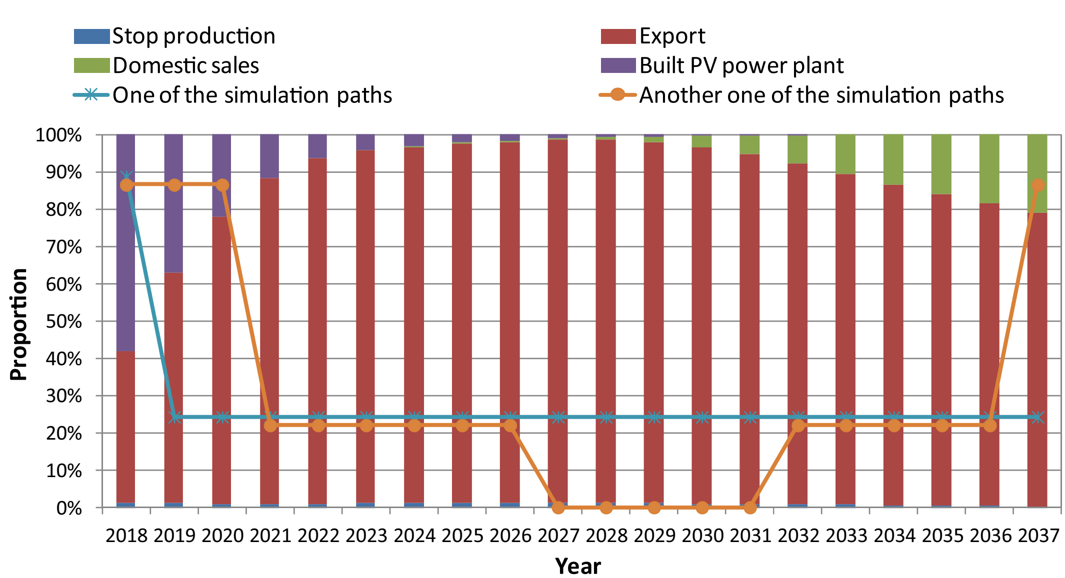

Fig. 2. Operational decision after investment.

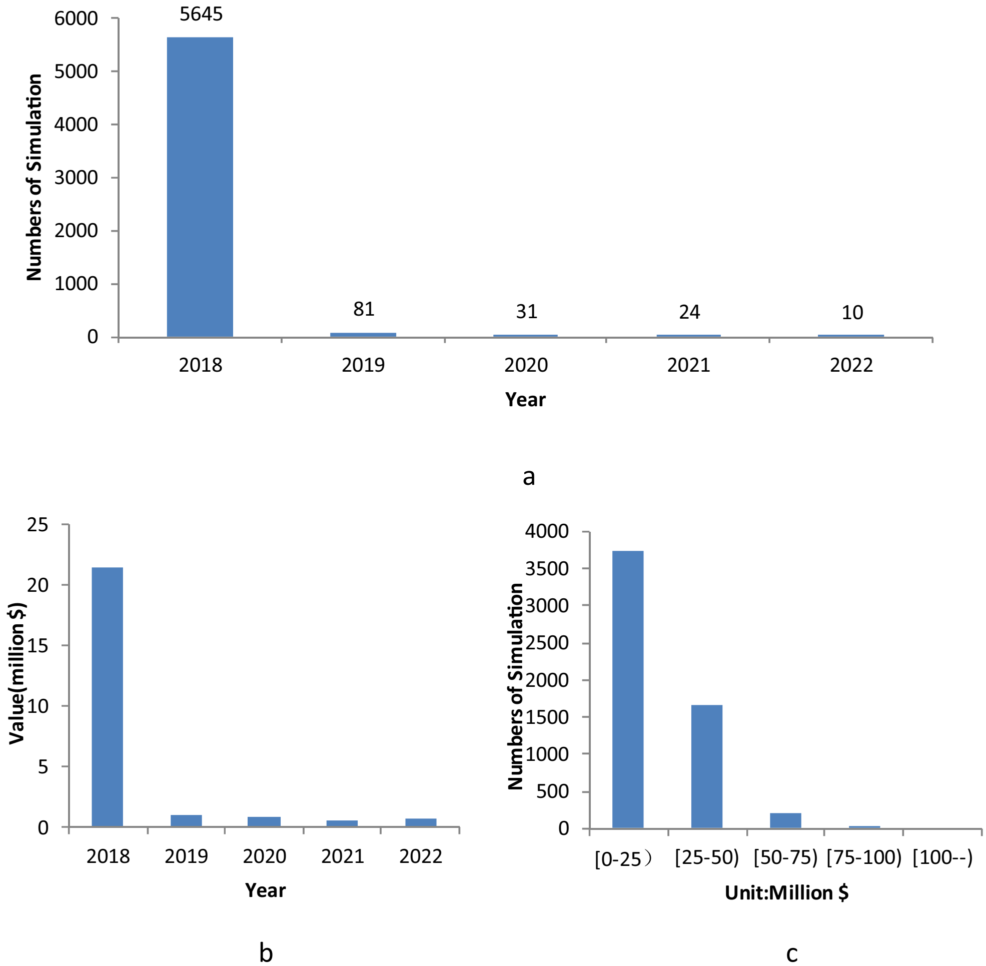

Fig. 3. a: Simulation results of investment year. b: Per simulation investment return. c: The distribution of investment return in the optimal year.

higher return can be found in S1, although the number of investments with lower return still dominates (3750 simulations in Fig. 3c).

In terms of operational decisions once the investment is made in 2018, Fig. 4 shows a dominant share of export since 2019 until the end of our simulation period. In 2018, the optimal choice for our solar panel producer is investment in a solar power plant, as the FIT remains attractive. With decreasingly protective trade measures, it becomes more profitable after 2019 to export solar panels produced by the new production line.

4.3. Scenario 2: constant FIT

With a constant FIT at the 2018 level (0.675 Yuan/kWh), 9866 of the 10,000 simulations choose to invest in building a new production line,

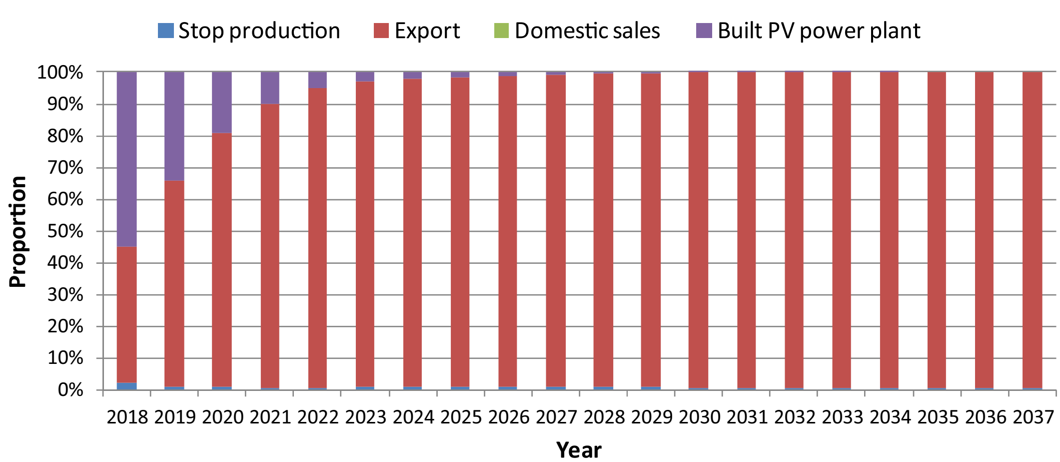

Fig. 4. Operational decision after investment.

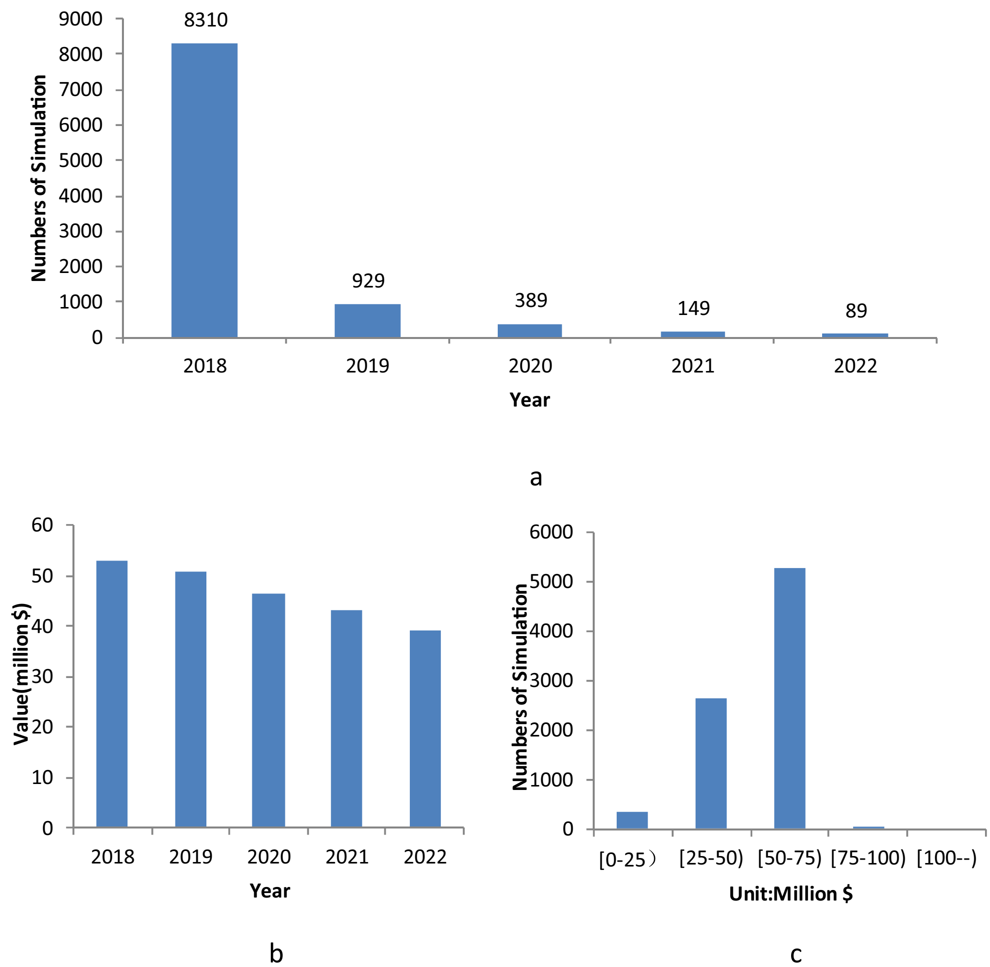

Fig. 5. a: Simulation results of investment year. b: Per simulation investment return. c: The distribution of investment return in the optimal year.

of which 8310 simulations lead to an immediate investment in 2018 (Fig. 5a). Comparing to previous scenarios, the investment risk is very low if the FIT becomes constant during the simulation period. The average return of early investment in 2018 is still higher than that of later investments, while the difference of returns among diverse investment years decreases (Fig. 5b). This is mostly due to the constant FIT that provides insurance for the solar panel market.

Different from previous scenarios, a majority of the simulations of investment in 2018 lead to a region of medium-level investment return (Fig. 5c): 5259 simulations generate returns that fall into the region of 50–75 million US$, while only 337 simulations have returns lower than 25 million US$. Still, only a few simulations lead to a higher return.

As Fig. 6 shows, the rational choice for solar panel producers is evidently to build a solar power station with the producer's own solar

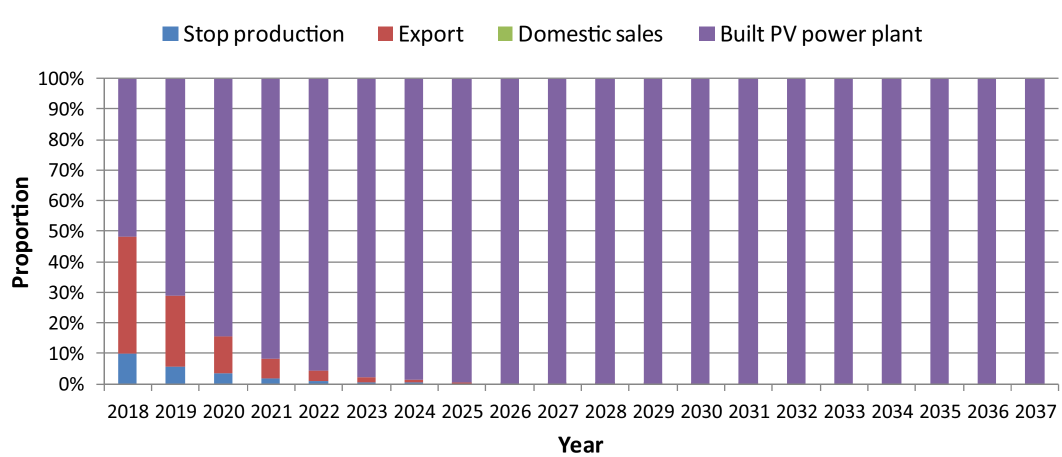

Fig. 6. Operational decision after investment.

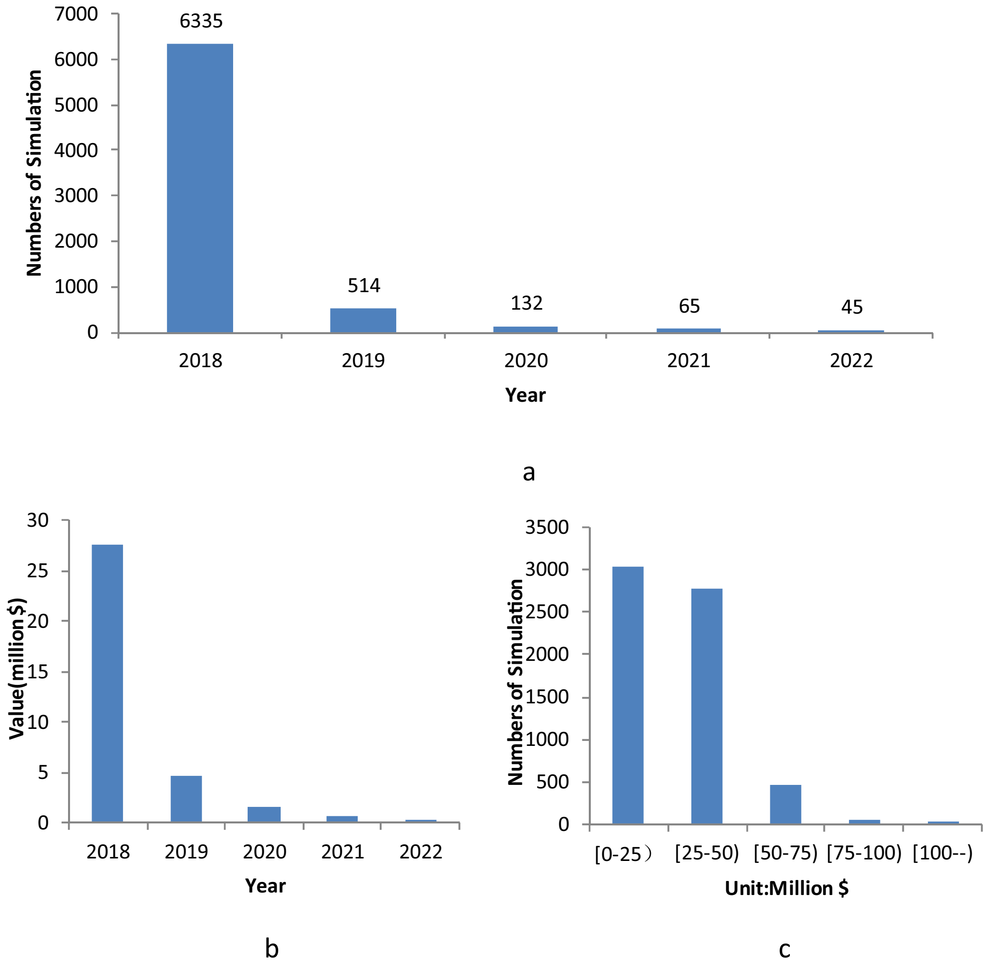

Fig. 7. a: Simulation results of investment year. b: Per simulation investment return. c: The distribution of investment return in the optimal year.

panels to benefit from the FIT during the simulation process. Stop production occupies a certain proportion in early years because the FIT fixed at 0.675 Yuan/kWh (the expected FIT level of year 2018 in S0) and it is lower than the FIT level of year 2017. So in some simulated paths the producer chooses to stop production when the FIT level does not meet its expectation, and the portion of "stop production" paths can to some extent illustrate the risk of the investment. The decision of building production line is based on the prediction of the producer for a period of time in the future, and the decision of stopping production is based on the simulated situation of the year. Such a scenario is unlikely to occur in reality, as costs are supposed to continue to decrease. It shows, however, the importance of the FIT as a governmental subsidy for the investment choices of solar panel producers.

4.4. Scenario 3: lower investment cost

In this scenario, it is assumed that government implements supply-side supportive policies to cut the investment cost by half. As Fig. 7a

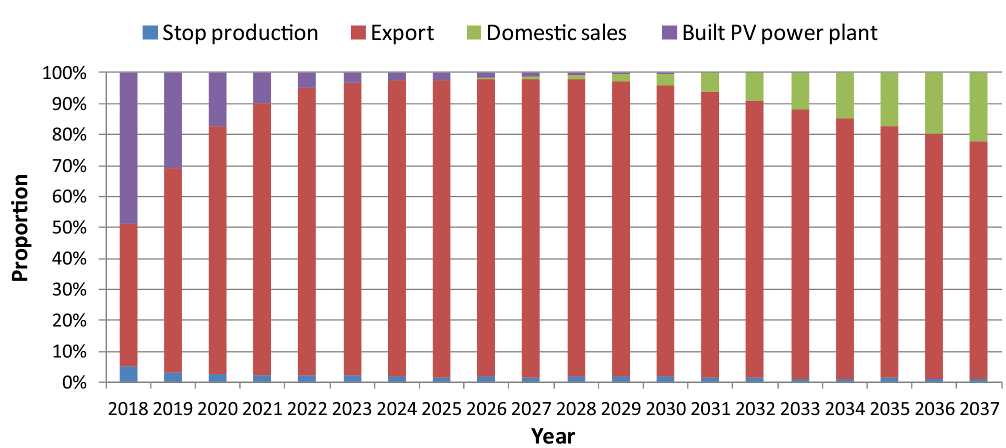

Fig. 8. Operational decision after investment.

Table 2
Comparison among scenarios.

Scenario	S0	S1	S2	S3
Average investment return in optimal investment year (million US$)	18.80	21.43	51.61	27.56
Investment uncertainty (%)	46.73	42.09	1.34	29.09
Project value without options (million US$)	4.84	8.77	51.30	18.00
Option value (million US$)	13.96	12.66	0.31	9.56

shows, an important number of simulations choose to invest in 2018. In addition, as shown by Fig. 7b, the average investment return corresponding to investment in 2018 remains much higher than investments in other years (similar to S0 and S1).

In S3, the numbers of simulations of 2018 investment that generate low and medium returns are closer: 3039 simulations with return lower than 25 million US$ and 2777 simulations with return between 25 and 50 million US$, while only a few simulations provide higher return. This result is quite logical, as the low investment cost ensures a higher return, other things being equal.

As supply-side supportive policy entails no impact on demand-side policies and conditions, the operational choice in S3 is the same as that in S0 (Fig. 8). Lower investment cost can reduce the investor's expenditure of 3.7 million dollars. Compared to S0, the investment return in S3 is increased by 8.76 million. Appropriately reducing investment costs can reduce risks and encourage investors to participate in the market and obtain more benefits.

4.5. Comparison among scenarios

Table 2 summarises key results among the scenarios. We have calculated the project return without options among the scenarios by assuming that the investment should be made in the first year in all the simulated paths without any deferring of investment. The difference between the average investment return and the project return without options is defined as the option value, which is brought by the option to defer the investment, as we modeled. A higher option value indicates lower investment certainty. For example, the option value in S0 is 13.96 million US$, the flexibility of investment deserves serious consideration of the strategy on the part of the investors. In S1, the option value is 12.66 million US$, a relatively high level. A steady anticipation of the continuous decrease of protective trade measures could not entail a dramatic increase in the frequency of the investment decision as a result of the change in destination countries from Europe and the US to other countries (developing countries in particular). In S2, a constant FIT provides insurance for investors with a very low option value. A medium investment uncertainty with medium option value is found in S3.

5. Sensitivity analysis

In this section, we provide the results of sensitivity analysis for a few key parameters. First, switching cost (*SC*) represents the sales and operational capabilities of an enterprise. In our model, SC is set at 5%. Fig. 9 shows the correlation between SC and investment risk and return. As shown, a higher switching cost leads to lower investment return and

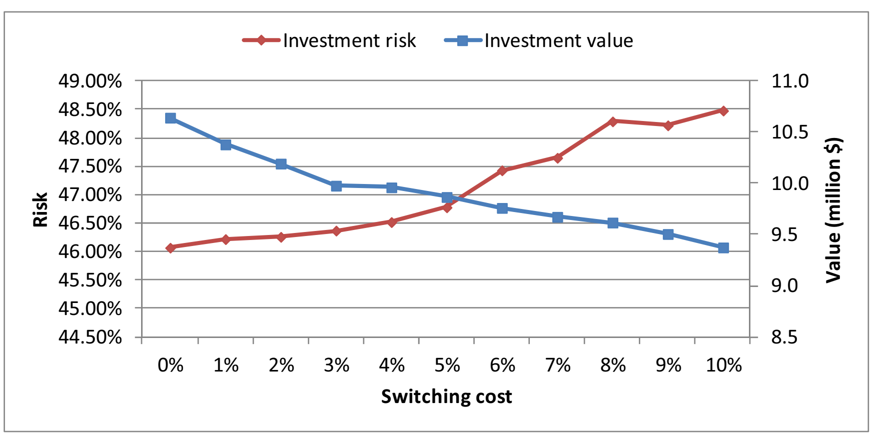

Fig. 9. The influence of different levels of switching cost.

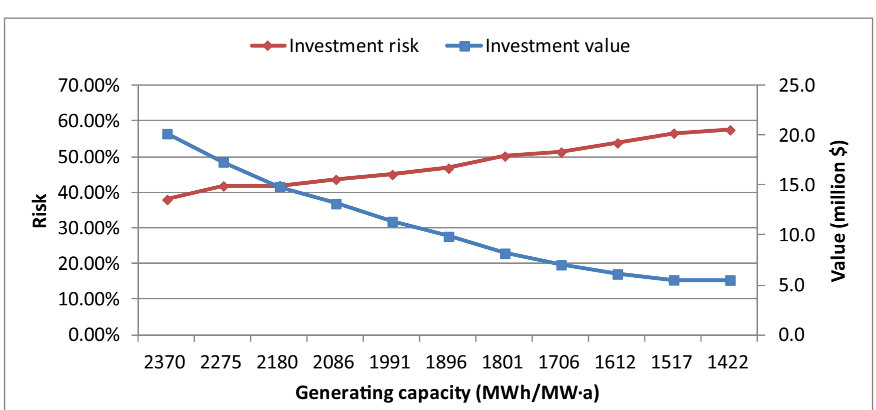

Fig. 10. The influence of generation capacity.

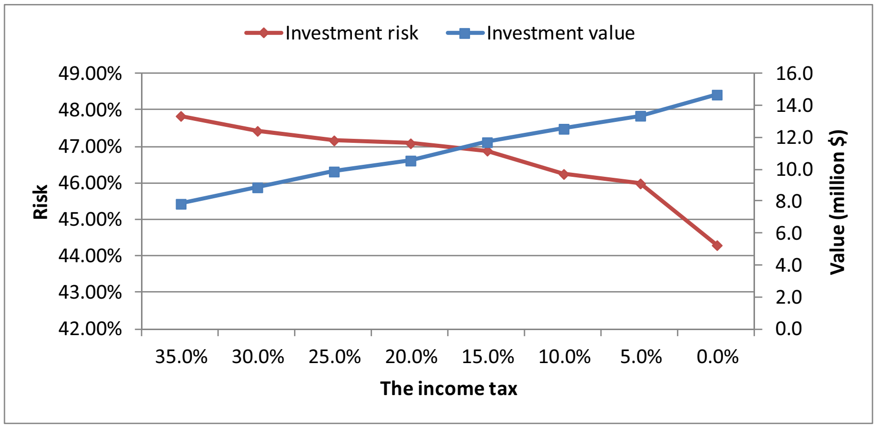

Fig. 11. The influence of income tax.

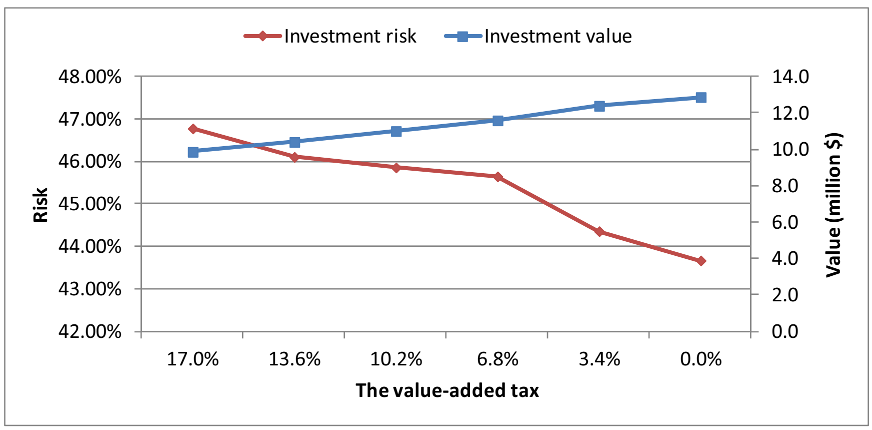

Fig. 12. The influence of value-added tax.

higher risk. A change of 20% of SC generates merely a change of 1% and 2% in investment return and risk, respectively, indicating a low sensitivity.

Second, photoelectric conversion efficiency reflects the technical level of a photovoltaic manufacturing enterprise, and it is set at 1896 MWh/MW · a in our model. Fig. 10 shows that a change of 5% in photoelectric conversion efficiency leads to a change of 4% for investment risk and 10% for investment return.

Third, the income tax and value-added tax will affect the profit of the photovoltaic enterprise. In this respect, if it is necessary to protect the photovoltaic industry, the government can easily make changes. In our model, the income tax and value-added tax are set at 25% and 17%, respectively. As Fig. 11 shows, a change of 10% of the income tax leads to a change of 1% for investment risk and 10% for investment return. Fig. 12 shows that a change of 20% of the value-added tax leads to a change of 1% for investment risk and 5% for investment return. In general, the income tax and value-added tax will hardly affect investment risk. In addition, the income tax has a significant impact on the income of the project.

Finally, the average levels of anti-dumping duty and countervailing duty, *Tr*, is related to export profit. According to the historical data, the value of *Tr* in 2018 is 8% in our model and the probability that *Tr* remains unchanged is 50%. The Fig. 13 shows that a change of 10% of the

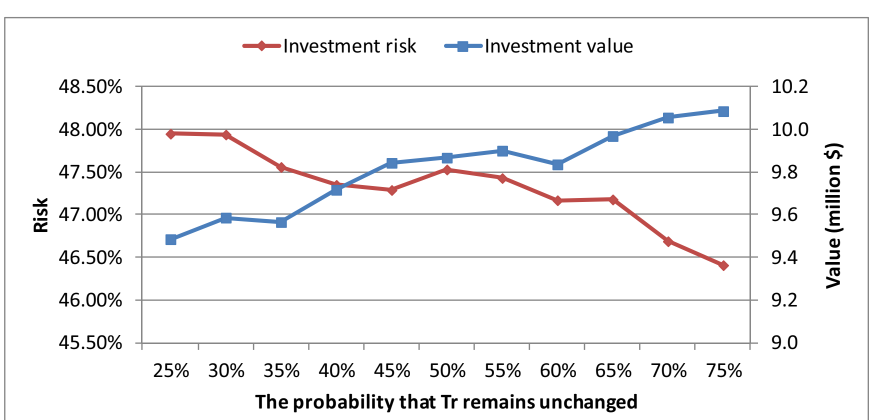

Fig. 13. The influence of the probability that *Tr* remains unchanged.

probability leads to a change of 1% for investment risk and 1% for investment return. The assumption that the probability of *Tr* remains will not have significant impact on the results.

6. Conclusion

This paper analyses the investment decision-making of Chinese PV module manufacturers with a real options method. With simulations on both the supply- and the demand-side of solar panel, it shows how a typical solar panel producer adjusts his investment choice and how these policies influence the solar panel producer's profit. This analytical framework helps policy makers understand at a firm level how modification and/or implementation of policies could impact solar producers. It also provides a reference for solar panel manufacturers to assess and simulate investment strategies in the future with public policy uncertainties.

There is room for improvement in this article. In addition to data constraints, this paper focuses on solar panel manufacturing and does not assess further production chain decomposition (from crystalline silicon, wafer to cell). The model in this paper is a simplified optimisation assessment that provides a single choice of investment decision. In reality, there exist cases where both export and domestic sales and even investment in solar power plants occur at the same time for one solar panel manufacturing company. This requires a further enrichment of the model.

Acknowledgement

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Appendix A

A.1. Annex 1 Deduction of Eq. (3)

P_t^{In}, P_t^{Do} and C_t^{P} all follow GBM. Here, we take the formula deduction of international price as an example. Let $X_t \equiv lnP_t^{In}$, and applying Ito's Lemma, we obtain:

$$dX_t = \left[\frac{\partial X_t}{\partial t} + \frac{\partial X_t}{\partial P_t^i}\cdot u_{In}\cdot P_t^i + \frac{1}{2}\left(\sigma^i \cdot P_t^i\right)^2 \frac{\partial^2 X_t}{\partial {P_t^i}^2}\right]dt + \frac{\partial X_t}{\partial P_t^i}\cdot\sigma^i\cdot P_t^i\cdot dW_t^i \qquad (A-1)$$

Because

$$\frac{\partial X_t}{\partial t} = 0 \qquad (A-2)$$

$$\frac{\partial X_t}{\partial P_t^{In}} = \frac{1}{P_t^{In}} \qquad (A-3)$$

$$\frac{\partial^2 X_t}{\partial {P_t^{In}}^2} = -\frac{1}{\left(P_t^{In}\right)^2} \qquad (A-4)$$

Then, we can obtain:

$$dX_t = \left(u^{In} - \frac{(\sigma^{In})^2}{2}\right)dt + \sigma^{In} dW_t{}^{In} \qquad (A-5)$$

The risk-neutral version of this equation becomes:

$$d\hat{X}_t = \left(u^{In} - \frac{(\sigma^{In})^2}{2} - \lambda\right)dt + \sigma^{In} dW_t^{In} \qquad (A-6)$$

where λ denotes the risk premium.
With $X_t \equiv lnP_t^{In}$ and dW_t^{In} as the increment of a standard Wiener process, we have:

$$d\hat{X}_t = X_{t+1} - X_t = lnP_{t+1}^{In} - lnP_t^{In} \qquad (A-7)$$

$$dW_t^{In} = \varepsilon(dt)^{1/2} \qquad (A-8)$$

From formulae (A-7) and (A-8), we can obtain the result:

$$P_{t+1}^{In} = P_t^{In}\cdot exp\left[\left(u_{In} - \frac{(\sigma_{In})^2}{2} - \lambda\right)\Delta t + \sigma_{In}\varepsilon(\Delta t)^{1/2}\right] \qquad (A-9)$$

Similarly, the domestic price and production cost can be obtained as:

$$P_{t+1}^{Do} = P_t^{Do}\cdot exp\left[\left(u_{Do} - \frac{(\sigma_{Do})^2}{2} - \lambda\right)\Delta t + \sigma_{Do}\varepsilon(\Delta t)^{1/2}\right] \qquad (A-10)$$

$$C_{t+1}^P = C_t^P \cdot exp\left[\left(u_P - \frac{(\sigma_P)^2}{2} - \lambda\right)\Delta t + \sigma_P \varepsilon (\Delta t)^{1/2}\right] \tag{A – 11}$$

A.2. Annex 2 Calculation of the drift rates and the volatility rates

Let us take P_t^{In} as example. We know the relationship between P_{t+1}^{In} and P_t^{In}:

$$P_{t+1}^{In} = P_t^{In} \cdot \ exp\left[\left(u_{In} - \frac{(\sigma_{In})^2}{2} - \lambda\right)\Delta t + \sigma_{In} \varepsilon (\Delta t)^{1/2}\right] \tag{A – 12}$$

There exist two ways to estimate the parameters of $u_{In} - \lambda$ and σ_{In}. One is the minimisation of the sum of squared errors (the differences between the future model price and the observed market price); another is to apply Kalman filter estimates. Here, we use the first method. First, calculate U_{In} with actual data:

$$U_{In} = X_{t+1} - X_t = lnP_{t+1}^{In} - lnP_t^{In} \tag{A – 13}$$

$\overline{U}$ is the mean value of U_{In}. S^2 is the variance.

$$\overline{U} = \sum_{i=1}^{n} U_{In}/n \tag{A – 14}$$

$$S^2 = (n-1)^{-1} \sum_{i=1}^{n} \left(U_{In} - \overline{U}\right)^2 \tag{A – 15}$$

From formula (A-6), we have:

$$E(U_{In}) = \left(u_{In} - \frac{(\sigma_{In})^2}{2} - \lambda\right)T \tag{A – 16}$$

$$Var(U_{In}) = (\sigma_{In})^2 T \tag{A – 17}$$

And we obtain the following equation:

$$\overline{U} = E(U_{In}) = \left(u_{In} - \frac{(\sigma_{In})^2}{2} - \lambda\right)\Delta t \tag{A – 18}$$

$$S^2 = Var(U_{In}) = (\sigma_{In})^2 \Delta t \tag{A – 19}$$

After this, we have:

$$u_{In} - \lambda = \frac{\overline{U} + S^2/2}{\Delta t} \tag{A – 20}$$

$$\sigma_{In} = S/\sqrt{\Delta t} \tag{A – 21}$$

According to the international price we obtain from the Wind Database in Table A1, we can obtain $\overline{U} = -0.0166$ and $S^2 = 0.0011$ for monthly data. Apply these two levels to formulae (A-20) and (A-21) with $\Delta t = 1/12$. To forecast the future market, we reduce the drift rate by half. Therefore, we obtain $u_{In} - \lambda = -0.096$ and $\sigma_{In} = 0.113$.

Similarly, based on data shown in Tables A2 and A3, we can obtain $u_{Do} - \lambda = -0.118$, $\sigma_{Do} = 0.084$ and $u_P - \lambda = -0.143$, $\sigma_P = 0.192$ for the domestic price and production cost, respectively.

Table A1
International price data.

Date	Price ($/W)	Date	Price ($/W)	Date	Price ($/W)	Date	Price ($/W)
2014–01	0.69	2015–01	0.59	2016–01	0.50	2017–01	0.39
2014–02	0.65	2015–02	0.57	2016–02	0.48	2017–02	0.36
2014–03	0.65	2015–03	0.55	2016–03	0.50	2017–03	0.36
2014–04	0.66	2015–04	0.55	2016–04	0.50	2017–04	0.36
2014–05	0.64	2015–05	0.52	2016–05	0.48	2017–05	0.36
2014–06	0.64	2015–06	0.57	2016–06	0.48	2017–06	0.35
2014–07	0.63	2015–07	0.53	2016–07	0.48	2017–07	0.35
2014–08	0.61	2015–08	0.54	2016–08	0.46		
2014–09	0.61	2015–09	0.52	2016–09	0.44		
2014–10	0.61	2015–10	0.52	2016–10	0.42		
2014–11	0.60	2015–11	0.50	2016–11	0.41		
2014–12	0.60	2015–12	0.52	2016–12	0.41		

Table A2
Domestic price data.

Date	Price($/W)	Date	Price($/W)	Date	Price($/W)
2015–07	0.551	2016–05	0.514	2017–03	0.349
2015–08	0.551	2016–06	0.512	2017–04	0.341
2015–09	0.553	2016–07	0.487	2017–05	0.336
2015–10	0.558	2016–08	0.467	2017–06	0.333
2015–11	0.56	2016–09	0.428	2017–07	0.329
2015–12	0.558	2016–10	0.399	2017–08	0.327
2016–01	0.554	2016–11	0.397	2017–09	0.323
2016–02	0.552	2016–12	0.384	2017–10	0.32
2016–03	0.547	2017–01	0.358	2017–11	0.315
2016–03	0.535	2017–02	0.354		

Table A3
The cost of production in China over time.

Date	Price($/W)	Date	Price($/W)
2007	4.80	2012	0.67
2008	3.20	2013	0.51
2009	1.70	2014	0.47
2010	1.40	2015	0.42
2011	1.09	2016	0.35

A.3. Annex 3 Calculation of annual power generation per megawatt PV module

Theoretically, under the known illumination conditions, the annual generation of photovoltaic panels can be obtained as:

$$\theta = Area \times AATSR \times TE \tag{A – 22}$$

where *Area* is the total area of 1 MW photovoltaic module; *AATSR* is the average annual total solar radiation; *TE* is the photoelectric transformation efficiency.

The area of a 235 W polysilicon photovoltaic panel is:

$$1.65 \times 0.992 = 1.64\,\mathrm{m}^2$$

1 MW photovoltaic modules require $1,000,000 \div 235 = 4255$ panels. Therefore, the total area of 1 MW photovoltaic modules (*Area*) is:

$$Area = 1.64 \times 4255 = 6965\,\mathrm{m}^2/\mathrm{MW}$$

We then obtain the average annual total solar radiation (*AATSR*).

$$AATSR = \sum (MADR \times NDM) \tag{A – 23}$$

where *MADR* is the monthly average daily radiation, and *NDM* is the number of days per month.

Let us take Shanghai City data as an example (shown in Table A4). The average annual total solar radiation (*AATSR*) is $5555\,\mathrm{MJ}/(\mathrm{m}^2 \cdot \mathrm{a})$. The photoelectric transformation efficiency (*TE*) is approximately 17.5%, obtained from industry experts.

We have:

$$\begin{aligned}\theta &= Area \times AATSR \times TE \\ &= 5555 \times 6965 \times 17.5\% \\ &= 6.771 \times 10^6\,\mathrm{MJ/MW \cdot a} \\ &= 1.896 \times 10^6\,\mathrm{kWh/MW \cdot a}\end{aligned}$$

Table A4
Monthly average daily radiation of Shanghai.

Month	1	2	3	4	5	6
$\mathrm{MJ}/(\mathrm{m}^2 \cdot \mathrm{a})$	12.236	14.397	16.381	18.158	18.961	18.383
Month	7	8	9	10	11	12
$\mathrm{MJ}/(\mathrm{m}^2 \cdot \mathrm{a})$	15.755	15.534	16.138	14.696	11.592	10.440

A.4. Annex 4 Calculation of AD & CVD (Tr)

Since 2011, the EU and the US have conducted successive anti-dumping and countervailing investigations on China. For China's PV industry, anti-dumping and countervailing duties (AD&CVD) on exported goods are only applied by the European and American markets. The rate multiplied by the proportion can be seen as the anti-dumping and countervailing duties on China's photovoltaic products. The tax rate of most of the surveyed enterprises is calculated as the AD&CVD of the year. Export data are derived from the China Photovoltaic Industry Association. The results of the past few years are shown in Table A5.

Table A5
Calculation of *Tr*.

Year	AD&CVD		Proportion of export sales		*Tr*
	EU	US	EU	US	
2013	11.80%	25%	24.0%	13.6%	6%
2014	56.30%	79.77%	13.9%	15.0%	20%
2015	56.30%	79.77%	10.4%	12.2%	16%
2016	56.30%	79.77%	4.4%	9.8%	10%
2017	56.30%	79.77%	3.0%	7.6%	8%

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